Artificial Intelligence in Brain-Computer Interfaces: Current Studies and Emerging Trends

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Abstract: Neurological disorders such as amyotrophic lateral sclerosis (ALS) or stroke impair the control of nerves over muscles, preventing people from living autonomously. Brain Computer Interface (BCI) offers a pragmatic answer, but suffers from scalability issues. This paper discussed the drawbacks of existing BCIs and how AI can be used in order to overcome them. By systematically reviewing and analyzing recent literature, this paper discusses how generative models and adaptive algorithms overcome the bottlenecks of traditional BCI. The combination of artificial intelligence (AI) and BCI solves the fundamental bottlenecks in traditional BCI, including low generalization capability, lack of sufficient data, and high cost. Generative AI-driven data augmentation improves the classification performance in BCIs up to 10-18%. The introduction of intelligent algorithms to adaptively optimize a BCI can significantly reduce its dial-in period, allowing it to operate without expert supervision while maintaining an adaptive response in real time.

Keywords: Brain Computer Interface, Artificial Intelligence, Machine Learning

1 Introduction

The human body requires a continuous interaction between the nervous and musculoskeletal systems for interacting with the world, requiring mobility and sensation. But if a serious neurologic disorder such as amyotrophic lateral sclerosis (ALS) or stroke occurs, this process is interrupted, representing a serious challenge in performing daily tasks or controlling external devices autonomously [1,2]. An alternative approach to overcome this limitation is provided through BCI systems, which are designed to translate the user's brain signal directly into actionable information that can be transmitted to an external device. More precisely, BCI aims at detecting brain signals that can reveal the intention of users so that the machine can know and perform some specified actions according to them. This gives hope to patients suffering from serious disability, offering an important lifeline of independence for people afflicted with neurological impairment via restoring communication/mobility.

Researchers have developed BCI in different parts of the world, including demonstrating real-time and accurate control of robotic hands with an electroencephalography (EEG) based BCI

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system, marking an important milestone in fine motor function restoration [3]. Another experiment is concerned with the role of the speech motor cortex for enabling BCI cursor control and click, expanding the set of tasks supported by BCI [4]. At the same time, BCI can also be used to rehabilitate patients, where one study focused on neural signal analysis in chronic stroke patients. It addresses the unique challenges of signal acquisition and decoding neural activities for patients with severe neurological damage, while contributing to important insight into furthering the development of intracortical BCI systems [5]. Taken together, these papers demonstrate how BCI can be used to regain function in cases where there are neurological deficits, while calling for additional work needed to improve its performance as well as its clinical utility.

The purpose of this paper is to discuss the shortcomings in classical BCI and introduce AI combined with BCI as a possible solution. Firstly, the paper will discuss how conventional BCI approaches are currently being developed, and what is lacking in these methods to make them widely applicable. Then, it will discuss a few recent works at the intersection of AI and BCI that demonstrate how generative models and adaptive algorithms addresses to the bottlenecks in traditional BCIs. In the end, we shall discuss some other issues that remain to be addressed in the integration of AI with BCI, as well as the trend of this field towards greater accessibility and clinical applicability.

2 BCI Development

BCI refers to an interface translating neuronal signals to tangible outcomes in reality, directly linking the human CNS with the outer world electronics [6]. BCI, as a tool, helps handicapped individuals compensate for their lost function by translating from neural signal to action command [1].

Currently, there are two kinds of BCIs, invasive and non-invasive. Invasive BCIs tend to show better performance than non-invasive BCIs in multiple tasks due to their higher spatial and temporal resolution of brain activity. However, it also acquires a higher risk of performing an implantation surgery to put the electrodes into the brain, which requires an extremely good medical condition [7]. In contrast, non-invasive BCIs mainly rely on the recordings of Electroencephalogram (EEG) signals by wearing a head cap of electrodes on the scalp of the patient, providing a safer and more practical solution. The problem is that the resolution of brain activity recorded is often low, along with a longer delay in time and lower accuracy in performance. However, despite having several decades of laboratory advancement, BCI has failed to achieve large-scale adoption by society, driving the urgent need of combining AI and BCI. The cause of this phenomenon (low social adoption of BCI) can be attributed to several challenges.

First, traditional BCI systems rely on discriminative models to record neural signals like EEG, with limited action commands and predefined categories in their fixed decoding algorithms. They can only recognize discrete intentions that had been presented in the past, while failing to capture the cognitive content that naturally emerges in the brain, such as language flow, visual scenes, and emotions. This makes them unable to adapt to real-life scenarios that are often complex in scope, lowering their capability to be applied to patients with severe health concerns.

Second, calibrating BCIs requires an excessive amount of EEG data from users and is constrained by factors such as ethics, costs, and sample sizes. Without enough data, the system's learning algorithms can't be trained, which are typically used to recognize the user's intentions. Moreover, the recording of EEG calibration data requires long periods of time, which is inconvenient for users, especially for patients with special medical or mental conditions.

Lastly, BCI systems with high resolution tend to have high costs too, and they are usually used in hospitals for clinical purposes. The system also has difficulties with subject variability, where data of subjects other than the user may not be available, resulting in a subject-dependent operation on the BCI system. Therefore, it's not suitable for everyday use, whereas the combination with AI can transform BCI from a lab-based technology to a practical tool.

3 The merger between AI and BCI

The integration between AI and BCI focuses on solving the core bottlenecks of BCIs, including poor adaptability, data scarcity, and high costs. Through various distinct combinations, each approach not only resolves technical limitations but also directly or indirectly reduces BCI's maintenance and operational costs, enhancing the accessibility of BCIs.

One possible combination between AI and BCI involves data augmentation and signal enhancement, aiming to reduce the number of sample data required and thereby cutting the costs associated with large-scale neural data collection (a major expense for traditional BCI). To achieve data collection within a minimal volume, filtering is required before the information is used for further applications. During this process, all the non-useful information was removed, while the rest of the neural data was used to train diffusion models. By learning the spatial/temporal distribution and biological characteristics of real neural activities, the model can generate synthetic data that are statistically alike with real neural activity, enhancing the recognition accuracy of the BCI system by 10–18% even when the size of generated data was over 4 times the size of actual recorded data [8]. Through combining real data with synthesized data, AI eliminates the need for costly data collection by constructing high-quality signals from non-invasive hardware, making it feasible under poor-resource conditions.

On the other hand, there is an alternative approach for combining AI with BCI based on deep RL that deals to the poor real world adaptability and frequent maintenance cost of conventional BCIs, for example, expert recalibration cost for making it work (major ongoing cost), and forms a closed loop enabling autonomous, real-time BCI adaptation without further manual interventions which increases the cost-effectiveness for such a system. Rather than just decoding neural signals so that people can move in reality (e.g., a computer cursor, a robotic arm), the AI & BCI work cooperatively to generate actions instructed by tasks. For instance, the AI would preprocess the data (task priority, previous movement, signal decode, etc.) and try to predict likely target and movement, and use it in completing the job, improving the task performance while not imposing extra cost to participants. Specifically, the AI was able to correct and infer the participant's goal, significantly decreasing the trial time by reducing the dial-in time to acquire the goal. In contrast to traditional BCIs, BCIs with the help of AI can reduce their dial-in time from a median of 4.15s to a median of 0.05s [9]. AI can also increase the efficiency of path trajectories, shortening the distance of paths by making them closer to becoming a straight line towards the target.

Both hybrid methods (generative AI & adaptive AI) overcome the limitations of classical BCIs, such as very high cost, poor accessibility, and flexibility across subjects. Expanding its environment from highly funded clinics into worldwide facilities, such as at-home usage or consumer markets, allows for a more widespread use of the BCI technology.

For instance, generative AI's data augmentation provides severely disabled patients (such as locked-in syndrome and ALS) another way to communicate with the world. From recorded EEG signals, the AI can generate audio recordings, which was thought to be an extremely challenging task given the complexity of human speech and the lack of technical skills to map these signals. Moreover, with the use of semantic classifiers, some AI can even generate images that were classified as having an accuracy of 85% [8]. This shows the high potential of combining AI with BCI, especially when considering that the AI only requires a small sample of neural data.

On the other hand, adaptive AI's expert-free and autonomous operation reduces the need for having one-to-one specialists to monitor and adjust the BCI system during therapy. This makes BCI therapies feasible for hospitals with limited access to medical resources, as well as physical and neurorehabilitation specialists. In addition to that, BCIs can help patients to restore their motor functions after exposure to diseases, which has already been applied to patients with brainstem strokes [5]. By combining AI with BCIs, the system can achieve real-time adaptive calibrations with high accuracy and precision, further ensuring the reliability of BCIs in medical facilities.

Finally, AI can help reduce the costs of BCI by reducing neural data collection and boosting performance. For traditional BCIs, large-scale neural data collection is needed to ensure high precision in outcome, which is extremely costly and time-consuming. Also, since BCIs are mainly used on patients with severe disabilities, massive data collection may not be feasible due to their health concerns, especially for invasive BCIs that requires a surgery implantation. To resolve this, AI can self-generate data based on the small samples being collected, decreasing the amount of data required. Furthermore, AI can increase the accuracy of BCIs, thereby replacing expensive traditional BCI hardware with devices that are relatively cheap, enabling a wider range of applications from clinical to individual use.

4. Challenges and Future Trends

Although many developments have been achieved for incorporating AI into BCIs, it is still a field that carries multiple unresolved technical and ethical concerns limiting further development [7]. One main concern lies in the use of dry electrodes rather than wet electrodes. Dry electrode systems offer greater portability and shorter setup time, where they are frequently plagued by poor signal quality and high noise levels when compared with the wet electrode system [10]. As a compromise between both of them, salt-based electrodes give a good signal quality compared to dry electrodes, but still with a lower difficulty than wet ones in terms of setup. However, they still have trouble in keeping signals stable over a period of time because of evaporation and the need for continuous water supplement, which lowers their possibility of clinic utilization, where accuracy and robustness are very crucial in situations like surgery. A further technical limitation involves the computational requirement of current AI models, whereby many DL methods rely on an enormous quantity of computing capability. As such, they are impractical for mobile and wearable BCI applications, which are constrained to a very limited footprint, thus reducing the feasibility of this kind of combination [10].

However, the emergence of AI-based BCI also raises concern on some critical ethical and social aspects, such as mind privacy or user agency [10]. Given that BCI provides access to one's neural activity, the potential for abuse, as the high sensitivity of brain signals might raise issues about privacy (since it could capture people's inner thoughts and feelings). This highlights one major security issue for the cybersecurity of modern BCIs and raises concern about damage due to unauthorized access, data processing, and adversarial attack. Also, there are concerns among others about how an AI-based BCI system can affect or manipulate the user's intention to hijack their decision-making process in an intrusive and ethically unacceptable manner. This is compounded by a general opacity of most AI models that makes it difficult for users and clinicians to either fully comprehend or contest an algorithm's decision-making process. Combined, these issues also pose moral and safety questions regarding the utility of these technologies, particularly in healthy people, where risks are likely to outweigh their benefits.

5 Conclusion

This paper adopts a systematic review of shortcomings in conventional BCIs and explores what is happening with the convergence between AI and BCIs, including generative models and adaptive algorithms, that may overcome some of these bottlenecks in order to improve the practical performance of BCI technology.

In addition to the above issues, existing traditional BCIs (i.e., both invasive and non-invasive) suffer from a number of critical bottlenecks which limit their real-world applicability, such as a lack of generalizability to realistic environments, heavy dependence on large-scale and time-consuming data acquisition, and high prices which restrict them for clinic applications. Furthermore, conventional BCI with fixed decoding algorithms is capable of recognizing only a few predetermined intentions and cannot capture the abundant, cognitive contents generated naturally by the brain, e.g., language, visual scenes, emotion, etc., which makes them inadequate for various demands of severely neurologically impaired patients, limiting their applicability and generality. On the other hand, the synergy of AI and BCI can address these problems. Generative AI enables high-quality neural data augmentation, which considerably reduces the number of data recordings required to underpin functionality, or even allows for new functionalities like audio- and image-generation from EEG signals, which have been originally deemed as very hard tasks. On the other hand, reinforcement learning-based adaptive AI enables real-time autonomous calibration without expert help, significantly shortening the operation time and improving the overall task efficiency. Therefore, the AI-BCI combination will make the BCI system cheaper, stable, and flexible, extending the application field from laboratory and clinical scenarios towards personal and everyday use, usually targeting patients affected by severe neurological pathologies such as ALS or stroke.

The future work in this merge of AI & BCI should aim at creating lightweight AI models for use with wearable devices, as well as enhancing signal stability and quality of non-invasive electrodes to boost their day-to-day performance. Government or other bodies should have started formulating clear-cut ethics related to brain privacy, data security, and algorithm transparency in order to safeguard patients' rights completely. All together, they serve as a good promotion to the healthy and sustainable development of the AI-BCI system itself and expand its scope in the application field in real life.

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